Crop Stress Sensing and Plant Phenotyping Systems: A Review

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Abstract: Enhancing resource use efficiency in agricultural field management and breeding high-performance crop varieties are crucial approaches for securing crop yield and mitigating negative environmental impact of crop production. Crop stress sensing and plant phenotyping systems are integral to variable-rate (VR) field management and high-throughput plant phenotyping (HTPP), with both sharing similarities in hardware and data processing techniques. Crop stress sensing systems for VR field management have been studied for decades, aiming to establish more sustainable management practices. Concurrently, significant advancements in HTPP system development have provided a technological foundation for reducing conventional phenotyping costs. In this paper, we present a systematic review of crop stress sensing systems employed in VR field management, followed by an introduction to the sensors and data pipelines commonly used in field HTPP systems. State-of-the-art sensing and decision-making methodologies for irrigation scheduling, nitrogen application, and pesticide spraying are categorized based on the degree of modern sensor and model integration. We highlight the data processing pipelines of three ground-based field HTPP systems developed at the University of Nebraska-Lincoln. Furthermore, we discuss current challenges and propose potential solutions for field HTPP research. Recent progress in artificial intelligence, robotic platforms, and innovative instruments is expected to significantly enhance system performance, encouraging broader adoption by breeders. Direct quantification of major plant physiological processes may represent one of next research frontiers in field HTPP, offering valuable phenotypic data for crop breeding under increasingly unpredictable weather conditions. This review can offer a distinct perspective, benefiting both research communities in a novel manner.

Key words: crop stress sensing; plant phenotyping; variable-rate field management; HTTP system

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1 Introduction

Securing food supply to meet the population growth and economic development under a changing climate is vital for the stability and development of our society[1-3]. The dominant contribution of precise field management and crop breeding to the increase of the actual and potential crop yield is conclusive[4]. Continuously improving the utilization efficiency of agricultural inputs such as irrigation water, fertilizers, and pesticides plays an important role to close the yield gap[5]. Precision agriculture (PA) has been brought forward to realize a more sustainable crop production. Rather than applying irrigation water, fertilizers, and pesticides uniformly, these inputs are applied variably to match the spatial and temporal variability of crops and soil within the field[6]. Variable-rate (VR) application systems for irrigation, fertilization, and pesticides are carried out based on the soil and yield maps in the

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USA[7]. Numerous research projects have been conducted to quantify the real-time crop needs at high spatial and temporal resolutions to further improve the utilization efficiency of these input resources. VR field management involves three main phases, including raw data collection, application map generation, and application. Cameras with certain wavelength ranges have been widely used for raw data collection by sensing platforms like satellites, airplanes, drones, sprayers, and field robots[8-10]. Different platforms have pros and cons in data resolution and throughput, field coverage, cost, and field accessibility. Other sensors like light detection and ranging (LiDAR) have also been used to measure canopy structure parameters related to its growth condition[11]. Models and algorithms have been developed to convert raw data to application maps. For example, the distribution map of the normalized difference vegetation index (NDVI) could be generated by an aerial sensing platform following a standard process. Then, an application map is generated based on an empirical model between the NDVI value and the application rate of nitrogen fertilizer[12]. Similarly, other (a)biotic stresses can be quantified using appropriate sensing systems and converted to corresponding application maps for VR applications. The technologies for the application phase of VR field management are mature and commercially available[13, 14]. For example, the irrigation map is converted into the operating parameters of center-pivots to trigger the irrigation event. Although huge effort has been made in the sensing and decision-making tools for VR field management, continuous research is still needed to develop tools that are reliable, versatile, well-integrated and affordable for wide adoption by producers.

The optimal yield could not be achieved without continuously developing the desired seeds (e. g., climate resilient, disease tolerant, and high nutrition concentration). In the last decade, High-throughput plant phenotyping (HTPP), which focuses on selecting better-performance breeding lines in plant breeding using advanced sensing technologies, has made considerable progress by exploring suitable sensors, platforms, and data pipelines[15-18]. Usually, the HTTP systems require higher spatial resolution for small breeding plots than that of VR field management at the production scale. The most widely used sensors in HTTP are cameras and LiDAR, which measure the canopy morphology, reflectance, and height at high throughput. Contact-type sensors are utilized for measuring leaf and soil parameters at selected locations using in-field sensor networks or robots[19-21]. Drones, high-clearance tractors, unmanned ground vehicles (UGVs), and large-scale ground systems have been developed for HTPP applications[19, 22-24]. These sensing and data analytic tools of HTPP research could also be integrated into the raw data collection and the decision-making phases of VR field management. At the University of Nebraska-Lincoln (UNL), several ground-based HTPP systems were developed for different research scenarios.

This study aims to: 1) review the state-of-art sensing and decision-making technologies for VR field management; and 2) introduce the hardware and data processing pipelines of HTPP systems. We specifically examine crop stress sensing systems and their corresponding decision-making models for VR field management, focusing on irrigation scheduling, nitrogen application, and pest management. Subsequently, we present the hardware and data pipelines of three HTPP systems developed at the UNL. Considering the similarities between the sensing systems in these two application areas, we hope this review can help researchers compare methodologies in both domains to further advance the development of information systems for targeted applications. We also address the current bottlenecks hindering the wide adoption of HTPP systems and explore potential new research frontiers.

2 Crop stress sensing systems for VR field management

The main (a)biotic stresses in field crop produc-

tion include water, nutrient, and pests. A timely and accurate detection and quantification of these stresses is the first step to applying VR technologies. We divided this section into three specific topics and carried out the review work of the crop stress sensing systems along with the decision-making models for Variable-Rate Irrigation (VRI) scheduling, nitrogen (N) application, and pesticide spray.

2.1 Drought stress sensing and irrigation scheduling

Irrigation for crop production often consumes the largest amount of fresh water, and the crop yield could be negatively impacted without irrigation[25-28]. Therefore, new ways to improve irrigation management and water use efficiency could effectively address the ongoing water scarcity problem encountered by field crop production[29-31]. Table 1 lists the main sensing technologies for irrigation scheduling to apply water with constant and variable depths. We list seven methods from the experience-based one that does not require sensor usage (I1) to data-driven methods that utilize sensors and models (I2–I7). Feel and appearance (I1) has been applied historically to estimate soil moisture with producers' experience. Over or under irrigation often occurs using this method due to a lack of a quantitative measure of soil moisture. Spatial and temporal variation of soil water status within the field is one of the most important sources of information for VRI scheduling (I2 – I7). Extensive research has focused on investigating how this variation and the microclimate relate to crop water stress. Thresholds of soil water potential were identified as irrigation triggers for specific soil textures and crop types (I3)[32]. Crop water stress index (CWSI) has been developed to quantify drought stress using infrared thermometers and environmental data (I4)[33, 34]. Crop evapotranspiration (ET) has been modeled using basic weather data and crop coefficients for the irrigation scheduling (I5)[35]. These data-driven methodologies have realized a more accurate guidance of the irrigation scheduling[36]. In other words, I2–I5 focus more on the irrigation scheduling to meet the real-time demand of crops. These methods often lack the needed spatial resolution to vary the water application rate site-specifically (i.e., only a few locations in the field can be monitored).

I6 and I7 are two more advanced methods based on a combination of a mobile sensing platform and stationary sensor stations for VRI scheduling[37, 38]. I6 leverages the widely adopted center pivot irrigation systems as an integrated sensing and irrigation platform by mounting infrared thermometers onboard to measure the canopy temperature. An integrated CWSI was calculated to assess the spatial variation of crop water stress. Fully automatic VRI was realized by this method without the additional cost of a standalone sensing platform. I7 deployed an aerial sensing platform to capture the spatial variation of the canopy reflectance. A hybrid model was developed based on surface energy balance and soil water balance to model the spatial variation of the soil water dynamics.

In conclusion, precise and site-specific irrigation management is essential for improving water use efficiency in field crop production, especially in regions where drought events are becoming increasingly frequent. Timely and accurate quantification of crop drought stress and corresponding water needs is a challenging task, but it is necessary for effective irrigation scheduling. Our review highlights a range of irrigation scheduling methods, from traditional experience-based techniques to advanced data-driven approaches. In addition to considering spatial variations in soil properties and landscape, more advanced approaches utilize state-of-the-art remote sensing platforms and crop models to determine real-time crop water demand at high spatial resolutions. These data-driven methods provide a scientific foundation for moving towards fully automatic VRI systems.

Table 1 Sensing methods for irrigation scheduling using variable-rate irrigation (VRI) systems

Method	Name	Instrumentation	Extracted parameters	References
I1	Feel and appearance	None	Grower's observation	[39]
I2	Soil water balance	1. Neutron probe 2. Time Domain reflectometry 3. Capacitance probes 4. Tensiometers 5. Granular matrix sensors	1. Allowable soil water depletion 2. Soil water depletion	[36]
I3	Soil water potential	Granular matrix sensors	Soil water potential	[32]
I4	Crop water stress index (CWSI)	1. Infrared thermometer 2. Weather station	1. Canopy temperature 2. Weather data	[33, 34]
I5	Soil water balance with reference evapotranspiration (ET)	1. Soil water sensors 2. Weather station	1. Volumetric water content at root zones 2. Reference ET 3. Crop coefficient	[35, 40]
I6	Integrated CWSI	1. A wireless sensor network of Infrared thermometers 2. Weather station	1. Canopy temperature 2. Weather data 3. Volumetric water content at root zones	[37, 41-43]
I7	Soil water balance with canopy reflectance	1. Satellite imagery 2. Aerial imagery 3. Weather station 4. Neutron probe	1. Volumetric water content at root zones 2. Reference ET 3. Crop coefficient	[21, 38, 44, 45]

2.2 Sensing technologies for nitrogen application

High crop yield could not be achieved without applying the appropriate amount of fertilizers to the crops[46]. However, the loss of fertilizers to the environment through volatilization, surface runoff, and leaching has been a major contributor to the degradation of the soil and water resources[47, 48]. Potentially, excessive application of N fertilizer could lead to unsafe drinking water and food[49, 50]. Adequate application of N fertilizer is vital for the high yield of the non-legume crop in most scenarios. The main challenge is to decide the right amount of application rate for high yield, good economical return, and minimum negative environmental impact. Previous research found that a uniform N application could not achieve the best economical return and led to N-related pollution in overfertilized areas within a field[51]. Therefore, the site-specific application rates of N fertilizer need to be tailored to what the crop needs. In this section, we reviewed sensors and scheduling methods developed for VR N management (Table 2).

N deficiency often results in lower leaf chlorophyll content, which appears as reduced leaf greenness. Leaf color charts are used as an affordable but effective way to guide the application of supplementary N fertilizer (N1)[52]. The application of optical chlorophyll sensors improved N use efficiency in the field experiment (N2)[53]. Lab analysis of plant leaf tissues is considered the ground truth method to quantify plant N status (N3)[20]. Typically, plant leaves are sampled and sent to a commercial lab for the measurement of total N concentration on a weight (g/g) or area (g/cm^2) basis. However, this method is destructive, slow, labor intensive, with a low spatial-temporal resolution. Machine Learning (ML) algorithms have been applied to realize high-throughput and non-destructive estimation of leaf macronutrients using field spectroscopy (N4)[20]. A higher spatial resolution could be achieved by integrating this technology into robotic systems[19]. N5—N7 are high-throughput sensing methods at the canopy level that provide the high spatial-temporal resolution of the whole field for VR N application. A de-

Table 2 Sensing methods for variable-rate application of synthetic nitrogen fertilizer

Method	Name	Instrumentation	Extracted parameters	References
N1	Producer experience	Leaf color chart	Subjective leaf color	[52]
N2	Chlorophyll content	SPAD chlorophyll meter	Leaf chlorophyll content	[53]
N3	Lab analysis	Nitrogen analyzer	Leaf nitrogen concentration	[20]
N4	Leaf spectral scan	VIS-NIR-SWIR spectrometer	Leaf spectral reflectance	[20]
N5	Active-optical reflectance sensor (AORS) algorithm	Active two-band NDVI sensor	NDVI-related vegetation indices	[55, 56, 60]
N6	Extended AORS	1. Active three-band NDVI sensor 2. Electrical conductivity sensor 3. Weather data	1. NDVI-related vegetation indices 2. Soil texture, apparent electrical conductivity, bulk density, moisture, etc. 3. Growing degree day, precipitation, etc.	[57]
N7	Aerial platforms	Hyperspectral camera	Vegetation indices or reflectance spectrum	[58, 59, 61]

tailed review of active and passive sensing methods for this application was carried out[12]. Active spectral sensors have been developed specifically for this purpose which measures the spatial distribution of selective Vegetation indices (VIs). Sufficiency index (SI) is then calculated based on VIs of the reference strip or a virtual reference (N5). The N recommendation rates are then calculated from SI values using active-optical reflectance sensor (AORS) algorithms[54-56]. Outputs of active sensors are constant under varying illumination conditions and could be used at night. These sensors are usually integrated into boom sprayers for real-time VR N application. Economic and environmental benefits were found by applying this method in field experiments[54]. The spatial variation of soil properties and continuous weather data could further improve AORS performance (N6) [57]. Aerial sensing platforms (e. g., satellites, airplanes, and drones) provide a unique way to quantify the leaf chlorophyll content and biomass at the canopy level. Combined with ML algorithms, more complex models have been developed to estimate the plant N concentration (N7) [58]. Early-season plant N uptake could be estimated using hyperspectral images in the field condition[59]. A study also shows that nitrogen use efficiency increases when using sensing systems in a non-irrigated maize field, compared to conventional application methods[12].

In conclusion, achieving high crop yields in modern agriculture necessitates the sustainable application of adequate nitrogen levels. Excessive nitrogen application, however, can result in soil and water degradation and potential human health issues. Our review covers a range of sensing technologies and scheduling methods designed to address this problem, from cost-effective leaf color charts to sophisticated, integrated sensing and application systems. We anticipate that the development of novel sensors and more generalized models for variable-rate nitrogen scheduling will further minimize the negative impacts of nitrogen overapplication while maintaining high crop yields.

2.3 Biotic stress sensing for pesticide spray

Widespread use of pesticides undoubtedly increases crop yield by protecting it from devastating pest damage[62]. However, the level of pesticide residues entering food systems has to be strictly regulated by national agencies for human health while the intrusion of pesticides into the environment has been monitored. Pesticide pollution often occurs from non-point sources like surface runoff, leaching and drainage, and spray drift[63]. Pesticides were detected in surface and groundwater while higher concentrations are found in agricultural areas during the crop growing season[64, 65]. Spray drift could be minimized by using drift-reduc-

tion nozzles under optimal weather conditions[66-68]. Among many mitigation strategies to reduce the pesticide presence in water bodies, reducing the total application volume could be one of the most effective and practical ways[69].

Imaging sensors, especially RGB camera, is the dominant tool to detect biotic stress, given that the objects which cause the stress are often visible (weeds and insects). Table 3 summarizes the application of remote sensing methods and their processing algorithms to detect biotic stress for crop production. Commercial solutions for real-time spot-spray of weeds using boom sprayers are available from various vendors in recent years which could save up to 90% of herbicide usage (B1-B2[70]). Hyperspectral cameras have also been investigated for this task using ground platforms at the plant level[71-73] and airborne platforms at the sub-field level[74]. Traditional ML models were trained to classify plant types using the features generated from the input images[75]. Then those selected features or spectral reflectance are fed into a traditional machine learning (ML) model for classifying plant types. Usually, the processing is not computationally intensive compared to deep learning (DL) methods. DL algorithms have been proven as an excellent tool to accurately discriminate weeds from crops under complex nature illumination[76]. Light-weight field robots are another research focus to realize plant-level mechanical weeding to completely avoid herbicide needs (B3[77]). Aerial platforms with high-resolution cameras and advanced algorithms are potentially a universal sensing solution for field crop production in various scenarios[78]. B4 and B5 cover traditional ML and DL methods applied in the detection of crop disease and insect pests. Extensive effort has been made to improve the algorithm performance of the traditional image processing method under field conditions[79]. An interdisciplinary comparison was carried out for image processing techniques of the diagnosis of common human and plant diseases[80]. Public data sets of common plant diseases have been established to speed up the development of DL models[81]. Classification, detection and localization, and segmentation DL neuron networks have been applied in plant disease diagnosis and insect detection[82, 83]. Labeled data sets, which at the target spatial resolution and cover the entire development of the plant disease (high temporal resolution) and a wide range of field conditions (e.g., illumination and management practice), are the prerequisites to train more robust models[82]. Training models using cross-species data sets could also improve the model's performance[84]. Commercial satellite imaging networks now can produce multispectral global images every day at sub-meter resolution (B6) and significantly relieves the resolution bottlenecks of using satellite sensing systems in VR field management. Agricultural internet of things (Ag-IoT) networks could collect images at sub-leaf resolution to directly detect crop disease and insect pests (B7). Furthermore, it could monitor general crop growth by collecting crop-soil-environment data at strategically selected locations in a field[85].

In conclusion, remote sensing technologies like RGB and hyperspectral imaging, when combined with ML and DL algorithms, have demonstrated potential in detecting biotic stress and therefore reducing pesticide use. Notably, DL networks have been developed to guide real-time chemical application, significantly decreasing herbicide consumption. By deploying suitable platforms such as aerial platforms and field robots, as well as developing more accurate and universal models, we can effectively minimize crop biotic stress while preserving the environment.

3 Ground-based field HTPP systems at UNL

HTPP systems need to address various questions depending on the breeder's needs. Generally, they are used to help breeders to select better genotypes at specific breeding stages. Field HTPP systems usually utilize sensors, which have been seen in VR field man-

Table 3 A case summary in biotic stress detection for crop production

Method	Target stress	Name	Sensing instruments	Algorithm	References
B1	Weeds	John Deer's See & Spray	RGB camera	Deep learning	Vendor website
B2	Weeds	Trimble Agriculture's Weed-seeker 2	Active NDVI sensor	NDVI threshold	Vendor website
B3	Weeds	Small Robot Company's Tom and Dick	RGB camera	Deep learning	Vendor website
B4	Disease and insects	Traditional image processing	RGB, multispectral, hyperspectral, thermal cameras	Traditional and deep learning	[80, 86]
B5	Disease and insects	Deep learning—based diagnose	RGB camera, Hyperspectral camera	Deep learning	[81-83, 87]
B6	General crop status	High-resolution satellite network	Multispectral camera	Traditional and deep learning	[23, 88]
B7	General crop status	Ag IoT network	Various types of sensors	Traditional and deep learning	[85, 89]

agement, to quantify crop parameters that are important to crop breeders. Although similar sensor clusters can be used in both areas, HTPP systems generally require high spatial resolution and accuracy due to the small footprints of the breeding plot.

Distinct combinations of sensors and platforms yield unique advantages and disadvantages for HTPP systems. Generally, most HTPP systems utilize cameras and other sensors at varying spatial resolutions to measure similar phenotypic traits, such as leaf color and texture properties, canopy height and structure, canopy coverage rate, spectral reflectance, and canopy temperature. In current HTPP data pipelines, these traits are predominantly employed as selection criteria for crop breeding. Given the similarities in data formats and processing pipelines among HTPP systems, we present a comprehensive review of the primary sensors and their corresponding data pipelines used in HTPP research, illustrated through a detailed examination of three HTPP systems developed at UNL.

Fig. 1 shows these platforms and corresponding sensors. Various phenotypic traits could be collected by them, such as canopy coverage rate, temperature, spectral reflectance, and height. The greenhouse phenotyping system (Fig. 1(A)) captures multispectral and thermal images for experiment plots. The phenocart (Fig. 1(B)) can measure over 1500 breeding plots at a breeding location in one day. NU-Spidercam (Fig. 1(C)) is a large-scale cable-suspend field phenotyping facility with unique advantages. Main onboard sensors for each system are indicated in the corresponding sub-figures.

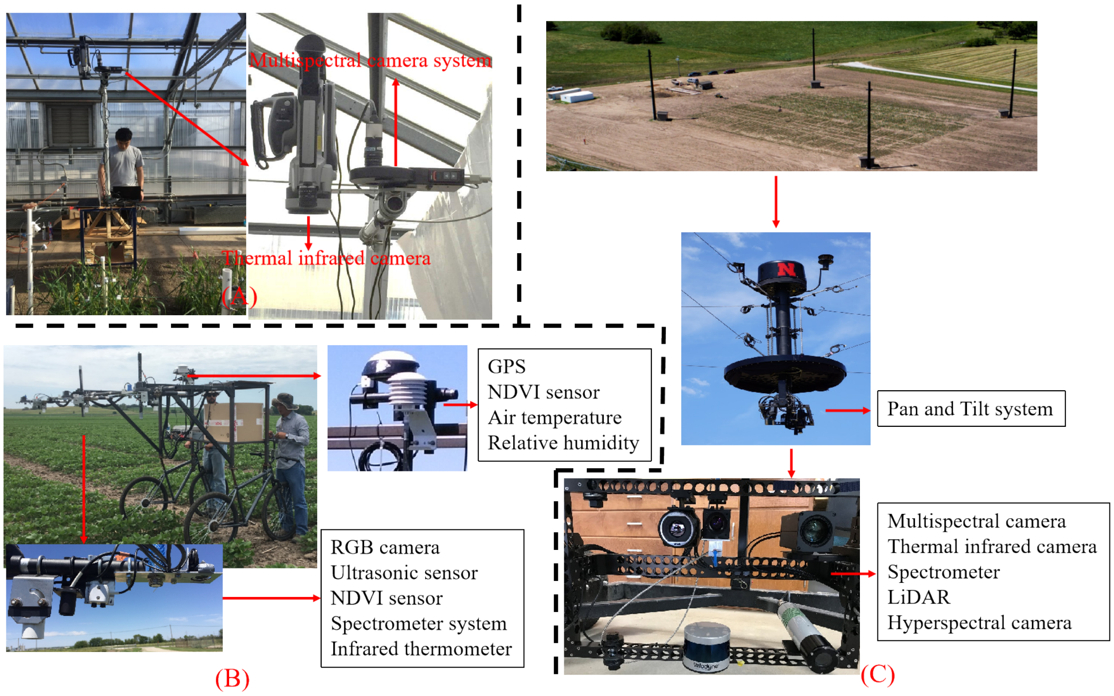
3.1 Multispectral−thermal platform

3.1.1 System components and raw data

The greenhouse phenotyping system was used to quantify the difference in drought dress of winter wheat plants under different irrigation treatments (Table 4)[90]. Canopy growth was quantified by calculating CWSI and growth index (GI) for each plot based on the multispectral and thermal images.

3.1.2 Data processing and data output

The experiment was conducted in a greenhouse with bare soil. The wheat genotypes with different drought stress responses were planted in 28 plots with a row spacing of 18 cm[90]. The plots were evenly split into drought and well-irrigated groups and raw images were collected multiple days across the growing period. Data pre-processing was carried out before the index calculation (Fig. 2). Image segmentation and regis-



Note:（A）a mobile platform for sensing drought stress;（B）a field phenocart for measuring various phenotypic traits;（C）a large-scale cable-suspended field phenotyping facility（NU-Spidercam）

Fig. 1 Ground-based HTPP systems developed at UNL

Table 4 Instrumentation of the greenhouse phenotyping cart

Camera type	Camera info	Other Parameters
Thermal camera	SC640, FLIR, OR, USA	640×480 pixels Canopy temperature
NIR monochrome camera	DCC3240N, Thorlabs, NJ, USA	1280×1024 pixels Canopy coverage
6-band filter wheel	FW102C, Thorlabs, NJ, USA	6 bands: 530, 570, 670, 770, 870, and 970 nm Canopy coverage and NDVI reflectance

tration were applied to extract the canopy coverage rate and the average leaf temperature. Air temperature and relative humidity were recorded by a standalone sensor station at the center of the experiment area. GI values were calculated by multiplying the canopy height and coverage rate. CWSI was calculated using the canopy and environmental parameters.

3.1.3 Result summary

The result shows that CWSI could differentiate the drought stresses between the given water treatments while the canopy coverage rate and GI could quantify the general plant vigor based on the correlation analysis between active NDVI sensors and the two parameters[90]. The system proves that a simple combination of two cameras could be used to identify drought-tolerant genotypes based on these phenotypic measures. More phenotypic parameters could be obtained by integrating more sensors. For example, the RGB-Depth camera could be used for canopy height measurement and coverage rate; Canopy structural parameters could be measured by LiDAR; Spectral reflectance of the canopy could be quantified using the hyperspectral camera. Little wind disturbance is an important advantage in the greenhouse, which has made important image processing processes (e.g., image registration) more accurate.

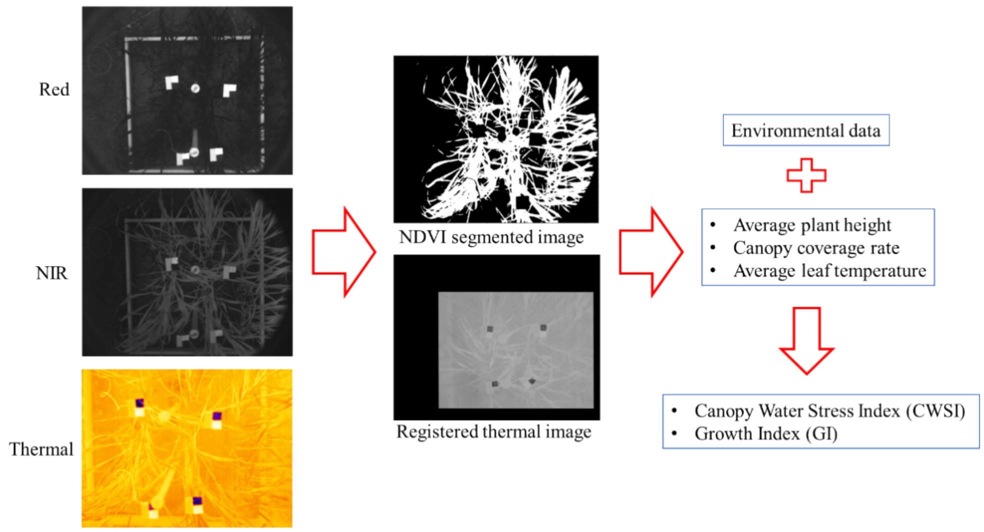


Fig. 2 The image processing protocol to calculate growth index (GI) and canopy water stress index (CWSI) by processing multispectral and thermal images with the environmental data

3.2 Integrated sensing platform-Phenocart

3.2.1 System components and raw data

A more complex phenotyping system was developed for HTPP under the field condition for multiple crop-site-year trials[91, 92]. Table 5 lists the onboard sensor types, detailed sensor information, and the extracted phenotypic parameters of the system. Multiple carts were built to support field breeding experiments of maize, soybean, winter wheat, and other crops.

Table 5 Instrumentation of Phenocart and corresponding phenotypic parameters

Sensor type	Sensor info	Other Parameters
RGB camera	C615, Logitech, Lausanne, Switzerland	1920×1080 pixels Canopy coverage
Ultrasonic sensor	ToughSonic30, Senix Corporation, VT, USA.	Canopy height
Thermal radiometer	SI-131, Apogee Instruments, Logan, UT, USA.	Plot temperature
NDVI sensor	SRS, Meter Group, WA, USA.	Plot NDVI
Spectrometer	CCS175, Thorlabs, NJ, USA	Plot reflectance
Air temperature and relative humidity sensor	HMP45C-L, Campbell Sci., UT, USA	Air temperature and relative humidity
GPS	AgGPS 162, Trimble Agriculture, CA, USA	Location and Timestamp

3.2.2 Data processing and data output

Raw RGB images for every breeding plot were stored in the root directory with a unique file name that indicates the plot number, experiment name, and timestamp. All other point measurements were recorded in a single data table in which each row represents the raw data of a point measurement. These data include the plot number, GPS coordinates, timestamps, height of the ultrasonic sensor, distance data from the ultrasonic sensor, plot temperature from the thermal radiometer, plot NDVI, plot reflectance, air temperature, and relative humidity. Fig. 3 illustrates the image processing pipeline for the automatic scoring of iron deficiency chlorosis (IDC) in a soybean breeding experiment[93]. The extracted color features using the protocol are used as inputs of statistical models to realize the ML-based IDC scoring.

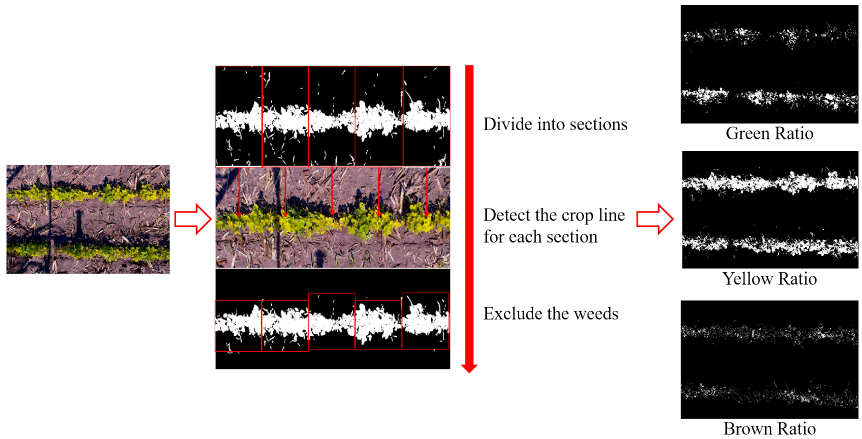


Fig. 3 The image processing protocol of automatic grading for soybean plots with stress from iron deficiency chlorosis (IDC)

3.2.3 Result summary

The multi-year data collection proves that phenocart is a reliable and relatively affordable HTPP tool for crop breeders to collect various phenotypic parameters[94]. The hardware and control software worked seamlessly and interactively with operators in the field condition. A reasonably high speed of about 0.2 ha/h was achieved by two operators manually pushing or pulling the cart in the field. The cart was also operated throughout the growing season for short-stature crops like winter wheat and camelina. The narrow tire width and protection cover minimized the plant damage during the data collection. The spatial resolution of the RGB images was excellent because of the close distance between the cameras and the canopy. The thermal radiometer measured the canopy temperature accurately although it could not distinguish the plant and soil targets within its field of view (FoV). In the later version of the phenocart, we replaced the ultrasonic sensors with a single LiDAR with 180° FoV perpendicular to the direction of the crop row. The LiDAR measured the canopy height more accurately than the ultrasonic sensor in a winter wheat experiment[92]. A good application of the phenocart was the automatic rating of soybean IDC stress[93]. By imaging soybean plots under IDC stress, a ML-based approach was taken to automatically score the IDC symptom (Fig. 3). The high prediction accuracy shows a great potential to integrate this work into breeding projects to improve screening efficiency.

3.3 Large-scale，cable-suspend phenotyping facility-Spidercam

3.3.1 System components and raw data

NU-Spidercam was built in 2017 at the Eastern Nebraska Research, Extension, and Education Center at UNL[95]. This cable-suspended sensing platform moves within a 0.4 ha scanning field precisely. In addition to environmental sensors, GPS, and other electronics, most of the sensors are mounted on a rotation frame which provides pitch and yaw flexibility. Table 6 lists the main instrumentation integrated into the NU-Spidercam. The raw data set includes multispectral images, thermal images, hyperspectral images, LiDAR point clouds, and the spectral reflectance. Frequent scanning of the whole field was carried out during the growing season. On each day, multiple measurements can be taken for each plot to track the diurnal dynamics of highly-variable phenotypic parameters.

3.3.2 Data processing and data output

All the raw data of one plot at a specific time was saved in a folder with a unique folder name. The folder name includes essential information including the time stamp, the plot number, the platform location, and sensor angles. Several phenotypic parameters were generated during the data processing. Fig. 4 gives a typical data processing pipeline for the multispectral camera, thermal camera, spectrometer, and the

Table 6 Instrumentation of NU-Spidercam HTPP facility

Sensor type	Sensor info	Other Parameters
Multispectral camera	AD080GE, JAI, Miyazaki, Japan	1024×768 pixel Canopy coverage
Thermal camera	A655sc, Teledyne FLIR, OR, USA	640×480 pixels Canopy and soil temperature
Spectrometer	HR2000+, Ocean Insight, FL, USA	Plot reflectance
LiDAR	VLP-16 Puck, Velodyne, CA, USA	Canopy height and structure
Hyperspectral camera	HSV101, Middleton, WI, USA	362—1043 nm Canopy reflectance

LiDAR. The canopy coverage rate was obtained by segmenting the plant pixels from the soil background in the multispectral images. Image segmentation and registration were applied to calculate the average soil and canopy temperature using the thermal image and the binary mask from the segmentation. NDVI, photochemical reflectance index (PRI), Red-Edge NDVI, soil-adjusted vegetation index (SAVI), and other VIs were calculated from the spectral reflectance from the spectrometer and hyperspectral camera. Canopy height was calculated from the LiDAR point cloud by subtracting the distance between the sensor and the canopy top from the distance between the ground and the sensor. All the parameters were output as a single data table with matched weather data which is delivered to the facility users.

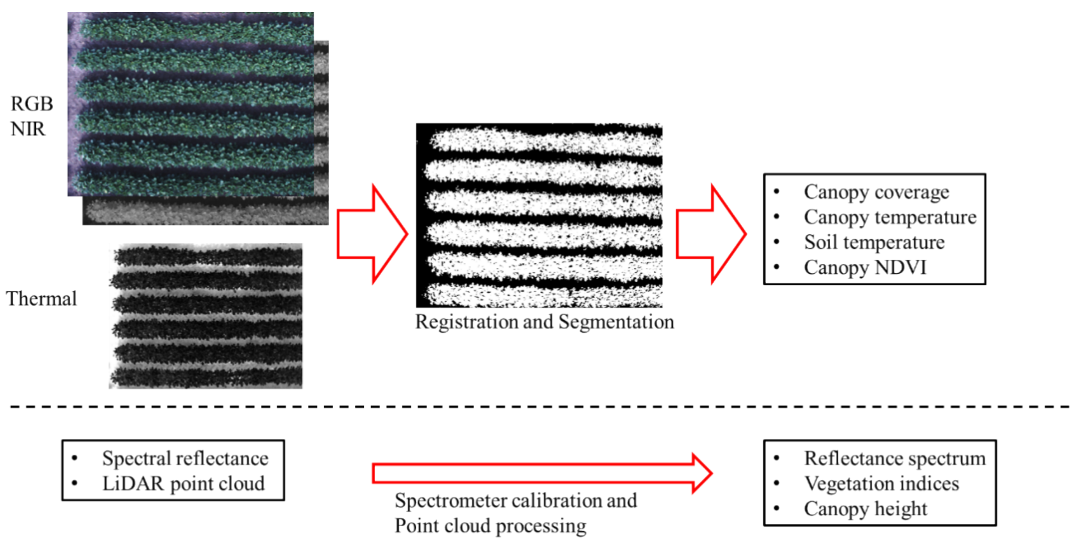


Fig. 4 Data processing pipelines for the onboard sensor cluster, including the multispectral camera, thermal camera, spectrometer, and the LiDAR

3.3.3 Result summary

NU-Spidercam has been successfully operated for 6 years without major issues. Effective wind protection structures were added to avoid cable wrapping on the poles due to the frequent strong wind at the facility site. Data collection can last for 6—8 hours without battery replacement with hot-swap capacity for extended collection duration. The performance of the platform positioning is accurate enough for the small plot study with an estimated accuracy of ±10 cm, given a plot size of 4.6 m by 6.1 m at the site. No crop damage was created by the sensing platform and the shadow of the platform was minimized. The platform can be raised up to 10 m above the ground which enables us to scan tall crops (e. g., energy sorghum) while keeping a wide sensor FoV.

4 Conclusion

The utilization of VR field management for irrigation water, fertilizers, and pesticides holds great promise in enhancing crop yield, optimizing resource use, and reducing adverse environmental consequences resulting from over-application. The increasing prevalence of climate change has led to heightened interest in sensing systems and their corresponding decision-making models. Concurrently, significant strides have been made in HTPP research, with the development of integrated sensing platforms and data pipelines for crop breeding aimed at bolstering phenotyping efficiency. Compared to VR field management, HTPP systems necessitate the detection of plant stress at a much finer spatial resolution. This review uniquely explores the sensing systems employed in both VR field management and HTPP systems. We initially examined crop stress sensing systems and their data pipelines for field crop production, concentrating on irrigation scheduling, nitrogen application, and pesticide spraying. Subsequently, we discussed the hardware and data pipeline of field HTPP systems by presenting three ground-based systems developed at UNL.

Significant advancements in field HTPP research for crop breeding have resulted from the interdisciplinary collaboration. It is anticipated that the integration of these platforms and data pipelines into crop breeding programs will enhance phenotyping efficiency, primarily by reducing labor costs and generating high-quality data sets. However, further improvements in their performance and cost are required to encourage widespread adoption. Overcoming challenges related to data quality, collection throughput, and processing pipeline efficiency is crucial for HTPP system optimization. The recent developments in artificial intelligence, robotic platforms, and innovative sensors are poised to enhance system performance and better support crop breeding decisions.

Optical sensors, particularly cameras capturing images at various wavelengths, are central to field HTPP systems due to their high-throughput capacity and spatial resolution. Conventional and DL-based computer vision algorithms allow for the accurate extraction of morphological traits from target canopies or individual plants as crucial phenotypic traits. These morphological traits are the cumulative product of major crop physiological processes such as ET, photosynthesis, and respiration. Developing phenotyping tools that can more directly quantify the physiological processes at the plot and plant level (real-time physiology phenotyping) will offer valuable insights for breeding climate-resilient varieties. Specifically, adapting sensing and modeling technologies from the remote sensing community to HTPP, with the support of high-resolution data sets, could facilitate a more direct estimation of these critical physiological processes (e.g., ET models and measurement of solar-induced fluorescence).

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作物胁迫感知和植物表型测量系统综述

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摘　要：提高农田管理的资源施用效率和持续培育优良作物品种是确保粮食产量和减轻作物生产对环境影响的关键途径。作物胁迫感知和植物表型测量系统是田间变量管理和高通量植物表型测量研究的核心，且两者在硬件和数据处理技术上具有相似性。几十年来，人们一直在开发可以用在田间变量管理领域的作物胁迫感知系统，旨在建立更加可持续的田间管理方案。与此同时，田间高通量表型系统开发取得的重大进展为降低传统表型测量成本提供了技术基础。本文首先对田间变量管理中涉及的作物胁迫感知系统进行了回顾，特别对目前用于精准灌溉、氮素施用和农药喷洒中的感知和决策方法进行了总结。基于作者团队在内布拉斯加大学林肯分校开发的三套田间表型测量系统，对常见田间高通量表型测量系统的传感器和数据的处理分析流程进行了介绍。此外，讨论了当前田间表型测量系统面临的挑战并提出了潜在解决方案。人工智能、机器人平台和创新仪器的持续发展有望显著提高测量系统的性能，对系统在育种中的大范围应用起到积极作用。对主要植物生理过程更直接的测量可能成为未来田间表型研究领域的研究热点之一，并为培育更耐胁迫的作物新品种提供有价值的表型数据。这篇综述可为田间变量管理和高通量植物表型测量两个研究领域提供参考和独特的见解。

关键词：作物胁迫感知；植物表型；田间变量管理；HTTP系统